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Citrus leaf disease detection through deep learning approach

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ABSTRACT

The majority of people in the world directly or indirectly depend on agriculture. Plant diseases are a significant threat to agricultural production and food security. Due to its high nutritional value, citrus fruit is one of the most abundant fruits in the world. However, different diseases are responsible for degraded citrus production as well as financial losses to the farmers. Traditionally, visual observation by experts has been attended to diagnose plant diseases. Usually, plant leaf disease recognition methods mainly rely on expert experiences to manually extract the colour, composition, and other features of diseased leaf images. Black spot, greening, canker, and melanoses are four common citrus leaf diseases. Rapid and accurate diagnosis of these diseases is a demand of time. Deep learning is a promising solution to these problems. There are different types of deep learning architecture like ImageNet, GoogleNet, VGG16, ResNet50, and InceptionV3, which show promising results in different object detection. Though most of these benchmark models give almost similar accuracy. However, this paper uses two deep learning models to find the better ones for the detection of citrus leaf disease detection. Hence, InceptionV3 outperforms VGG16 in terms of accuracy.

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1. INTRODUCTION

Agriculture research focuses on upsurging food production and eminence while dropping costs and increasing profits. In any state's economic development, fruit trees play a significant role. The citrus plant, high in vitamin C and commonly utilized in the Indian sub-continent, is one of the most familiar fruit plant species in the citrus family [1]. Citrus fruits and leaves are used to produce jams, candies, confectionery, and other agri-products that are beneficial to human health [2]. It was anticipated that Bangladesh would make 1.67 million tons of citrus in 2020 [3].

Black spots, cankers, scabs, and melanoses are just a few diseases that can plague citrus fruits. Citrus fruit defects cause a significant percentage of quality exports to be rejected each year. This means that early detection of citrus diseases can reduce losses and expenses while also enhancing the quality of the finished goods. However, the disease diagnosis process by humans is subjective, error-prone, slow, and costly. There will also be new diseases where no local specialist is available to deal with them [4]. An automated system is therefore urgently required. Automatic crop scanning has been made easier by the introduction of specialized equipment and computer-aided approaches [4]. Conventional machine learning algorithms have been successful for plant disease detection and diagnosis, but they are confined to sequential image processing tasks.

On the other hand, deep learning can automatically learn the hierarchical aspects of diseases, reducing the need to develop feature extraction and classification manually. More and more farmers and food producers are getting benefits from advances in deep learning techniques, such as identifying plant diseases [5]. A convolutional neural network model based on the latest scientific research is being presented to classify citrus diseases into four distinct groups: black spot, canker, scab, and melanoses. The symptoms of the diseased leaves and the images of four diseases are given in Table 1 with the content source.

Table 1. The symptoms of citrus leaf diseases

Source	Symptoms of the diseases	Image of the diseased leaves
Citrus black spot https://www.citrus.com/citrus-tree-care/pests-diseases/	Citrus black spot is a disease caused by the fungal infection of guignardia citricarpa.	
Citrus melanoses https://www.gardeningknowhow.com/edible/fruits/citrus/citrus-melanose-fungus.htm	Symptoms of citrus melanosis can be seen most clearly on leaves and fruit. The leaves develop small red-to-brown spots.	
Citrus greening https://crec.ifas.ufl.edu/hlb-information/greening/	Huanglongbing (HLB; citrus greening) is thought to be caused by the *bacterium candidatus liberibacter asiaticus*. The early symptoms of HLB on leaves are vein yellowing and asymmetrical chlorosis referred to as "blotchy mottle".	
Citrus canker https://idtools.org/id/citrus/diseases/factsheet.php?name=Citrus%20canker	Citrus canker lesions on the underside of a leaf typically range from 2 to 10 millimeters in diameter and have elevated concentric circles.	

The contributions of the study are as:

- This work presents VGG16 and InceptionV3 deep learning models for classifying diseases, such as black spot, canker, scab, and melanoses in citrus leaves.
- InceptionV3 gives a better performance than the VGG 16.
- The proposed method is automated, computationally efficient, and cost-effective to preserve the ecological and economic relevance of citrus plants and their yields.

The remainder of the research is structured as follows. The review of the literature is described in section 2. Section 3 explains the materials and methods. Section 4 presents and discusses the findings. Section 5 brings the research to a conclusion.

2. LITERATURE REVIEW

A brief description of the existing deep learning leaf disease identification approaches along with their merits and demerits are summarized in Table 2. From this literature review, we observe that there are scopes for accuracy enhancement and in-depth validation experimentation using extensive datasets. The present paper works on addressing these issues.

Table 2. A brief description of the existing state-of-the-art methods

Reference	Methods/architecture	Fruit/crop name	Accuracy	Limitations of the study
Moyazzoma *et al*. [6]	MobileNetV2	Cucumber	90.38	Give poor performance for unseen data
Singh *et al*. [7]	MCNN	Mango	97.13	Anthracnose/the missing report rate of 2.87%
Agarwal *et al*. [8]	EfficientNet	Apple, cherry, and potato	99.7	Plant diversity in the dataset is needed
Joshi *et al*. [9]	CNN	Vigna mungo	97.4	The model is not fully adaptable in real-time experiments
El-Maged *et al*. [10]	VGG16, CNN	Apple, cherry, potato	98.67	Don't explain the severity
Jasim and Tuwaijari [11]	CNN	Potato, tomato pepper	98.29	Multiple techniques are not used
Prakash *et al*. [12]	SVM	Citrus leaf	-	The number of images in the dataset is too few
Mohanty *et al*. [13]	AlexNet, GoogleNet	Strawberry, tomato, and potato	99.35	It has an over-fitting problem. Accuracy is different for different crops
Lee *et al*. [14]	VGG16, InceptionV3, GoogleNet	Cherry, apple, tomato, and grape	-	Diversity is needed in the dataset
Thangaraj *et al*. [15]	-	Tomato	99.18	Severity is not counted in this study
Hasan *et al*. [16]	CNN	Different types of crops	99.56	Accuracy decreases in real-time conditions
Kathiresan *et al*. [17]	-	Rice	98.79	The quality of some images in the dataset is poor
Arafath *et al*. [18]	VGG16, MobileNet, InceptionV3	Tomato	91.2	Plant village/small number of images are picked from the dataset
Saleem *et al*. [19]	-	-	99.81	More time is needed in each epoch
Ireri *et al*. [20]	SVM	Tomato	-	Accuracy decreases as the no. of grading categories are increased
Ghoury *et al*. [21]	Fastest R-CNN	Grape	99	Images in the dataset contain noise gives poor classification
Ramya and Jeevitha [22]	-	Plant species	-	A high-capacity cell phone is needed
Tahir *et al*. [23]	InceptionV3	Apple	97	Diversity in data is less available
Hassan and Maji [24]	VGG with Xgboost	Corn, potato, and tomato	97.36	The model is not good for lightweight devices
Saini *et al*. [1]	CNN, deep learning	Citrus leaf	95.65	The single dataset is considered, with only 213 images in the dataset
Janarthan *et al*. [25]	-	Citrus leaf	95.04	Heavy weight for lightweight devices
Rauf *et al*. [26]	-	Citrus leaf	-	Only a single dataset is used
Xing and Lee [27]	VGG19	Citrus leaf	95.01	Too bulky model, ill-suited for small dataset
Xing *et al*. [28]	DenseNet	Citrus pest		The size of the image is too large
Kukreja and Dhiman [29]	SGD	Citrus leaf	89.1	Fewer numbers of images in the dataset
Zheng *et al*. [30]	YoloV4	Citrus leaf	91.55	Manual labelling is needed
Qadri *et al*. [31]	MLP, RF	Citrus leaf	98.4	The disease is not detected.
Majid *et al*. [32]	-	Blueberry, apple, peach	99	Plant village/computational time is very high
Chen *et al*. [33]	VGG16, ImageNet	Rice, maize	92	The size of the model is heavyweight
Altinbilek and Kizil [34]	CNN	Rice	95.48	Dataset needs manual labelling
Chen *et al*. [35]	ImageNet	Rice	98.63	The model is heavyweight

3. METHODS AND MATERIALS

This section presents the methods and materials used in this research and the collected citrus diseased leaf images datasets as well as data augmentation.

3.1. Image acquisition

All phases of image analysis research necessitate data from training algorithms to evaluate their performance. From the citrus dataset [26] and the plant village dataset [36], a total of 1067 images were used. Images of sick citrus leaves were separated into four groups, each depicting a different disease. The disorders we researched include black spot, canker, scab greening, and melanosis (shown in Table 1). We used 80% of the data as training and 20% as testing. The environment used for the experiment is Google CoLab.

3.2. Image augmentation

Data augmentation in data analysis is the technique to increase the amount of data and is closely related to oversampling in data analysis [37], [38]. We use different augmentation techniques such as flipping, rotating, zooming, cropping, and colour varies. Table 3 shows the detailed picture of our investigated citrus disease dataset [27], [36].

Table 3. Description of the citrus disease dataset

Name of the disease	Number of images	Number of images after augmentation
Black spot	291	1000
Greening	310	1000
Canker	268	1000
Melanose	148	1640
Total	1017	4640

3.3. Proposed approach

The overall framework of the proposed method is given in Figure 1. We investigated two deep learning models: VGG16 and InceptionV3 using an Adam optimizer with a starting learning rate of 0.0001. The architecture of these benchmark deep neural models is shown in Table 4.

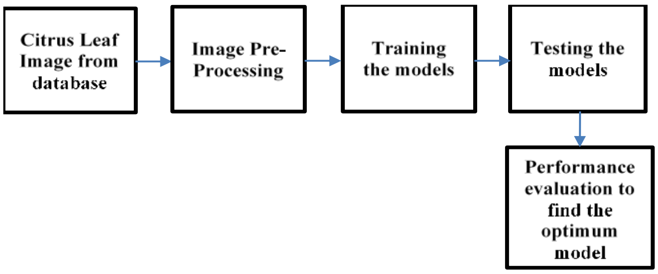

Figure 1. The framework of the proposed system

Table 4. Architectures of VGG16 and InceptionV3

	VGG16	InceptionV3
Input size	224×224	227×227
Convolutional layer	13	21
Filter size	3	1,3,5,7
Stride	1,2	1,2
Parameter	16817478	23×10^{6}
Fully-connected layer	3	1

4. RESULTS AND DISCUSSION

Accuracy indicates the percentage (%) of total data correctly identified by the classifier. Precision is the percentage of total anticipated positive data that were positives as determined by the classifier. The recall is the percentage of all positive data that the classifier correctly identified as positive. F1-score is the harmonic mean of precision and recall [39]. Mathematical representations of these metrics are shown in (1) to (4):

$$Accuracy\ (\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (1)$$

$$Precision\ (\%) = \frac{TP}{TP+FP} \times 100 \quad (2)$$

$$Recall\ (\%) = \frac{TP}{TP+FN} \times 100 \quad (3)$$

$$F1-score\ (\%) = 2 \times \frac{Precision \times Recall}{Precision+Recal} \times 100 \quad (4)$$

where true positive (TP) is the model predicts the correct sample as correct; true negative (TN) is the model predicts the incorrect sample as incorrect; false positive (FP) is the model predicts the incorrect sample as correct; and false negative (FN) is the model predicts the correct sample as incorrect. The class-wise TP, TN, FP, and FN are determined by using (5) to (8):

$$TP_i = c_{ii} \quad (5)$$

$$TN_i = \sum_{k=1,k\neq i}^{n} \sum_{j=1,j\neq i}^{n} c_{jk} \quad (6)$$

$$FP_i = \sum_{j=1,j\neq i}^{n} c_{ji} \quad (7)$$

$$FN_i = \sum_{j=1, j\neq i}^{n} c_{ij} \tag{8}$$

where *i* is the class and *n* is the total number of fruit classes. Here, C_{jk} is the component of the confusion matrix, *j* and *k* are the row and column of the confusion matrix [39].

Figures 2 and 3 show the confusion matrices of our investigated VGG16 and InceptionV3 models. Table 5 shows the accuracy, precision, recall, and F1-score of VGG16 and InceptionV3 models for all disease categories. This table confirms that InceptionV3 outperforms VGG16. In Table 6, we have compared the accuracy performance of our model with other related methods. Our model shows the best accuracy.

True label	Black Spot	Canker	Canker	Melanose
Black Spot	94	1	1	4
Greening	0	97	0	3
Canker	1	0	99	0
Melanose	2	1	1	160
	Predicted label			

Figure 2. Confusion matrix of VGG16 model

True label	Black Spot	Canker	Canker	Melanose
Black Spot	98	2	0	0
Greening	0	99	1	0
Canker	0	0	100	0
Melanose	0	1	0	163
	Predicted label			

Figure 3. Confusion matrix of InceptionV3 model

Table 5. Comparative result of VGG16 and InceptionV3 models

Diseases	VGG16				InceptionV3			
	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score	Accuracy
Black spot	0.97	0.94	0.95	0.98	1.00	0.98	0.99	1.00
Greening	0.98	0.97	0.97	0.98	0.97	0.99	0.98	0.99
Canker	0.98	0.99	0.99	0.99	0.99	1.00	1.00	0.99
Melanoses	0.96	0.98	0.97	0.98	1.00	0.99	1.00	0.99

Table 6. Performance comparison with the other methods

Reference	Methods	Accuracy (%)
Xing *et al*. [28]	CNN, deep learning	95.65
Kukreja and Dhiman [29]	CNN	95.04
Zheng *et al*. [30]	Machine learning	-
Qadri *et al*. [31]	VGG19	95.01
Majid *et al*. [32]	DenseNet	-
Chen *et al*. [33]	SGD	89.1
Altinbilek and Kizil [34]	YoloV4	91.55
Hughes and Salathe [36]	MLP, RF	98.4
Our model	InceptionV3	99

5. CONCLUSION

This research proposes a method for detecting four common types of citrus leaf diseases using two deep CNN models VGG16 and InceptionV3 utilizing transfer learning for better accuracy. Extensive experimentation was performed using two datasets. The VGG16 model exhibits 98% accuracy, whereas the InceptionV3 model exhibits 99% accuracy. Hence, InceptionV3 outperforms VGG16 in terms of accuracy. A comparison with the related methods confirms the effectiveness of InceptionV3 for citrus leaf-disease detection. In the future, we will work on the implementation of a real-time plant disease detection system in a mobile framework.

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